

## **The impact of minor injury unit closures on travel time and attendances**

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### **Abstract**

Geographic Modelling techniques provide a means of optimising the location of services, or understanding the potential impact of geographic service reconfigurations. In response to commissioner queries, we assessed the potential impact on patient travel time and attendances of the closure of four Minor Injury Units (MIUs) in a locality of South West England. We used the MPMileCharter add-in for Microsoft MapPoint and the attendance records of 90,252 Minor Injury Unit patients to calculate car travel time data to the units in the locality. We then built a Geographic Model of the existing configuration of MIUs in Microsoft Excel, and used “what if” analysis to determine the potential impact of the proposed closures. The model predicted that if the four MIUs were closed, there would be only a trivial increase in average travel time across all patients, but a

significant increase of around 20 minutes per patient for those whose nearest unit was closed. The model also predicted that the closure of one of the MIUs could lead to significant increased demand at the Walk-in Centre located at the acute hospital. Using these results, the local commissioners decided to close only three of the four units.

## **Introduction**

Geographic Models can be useful when trying to locate, close or geographically reconfigure services (McLafferty, 1988; Peleg and Pliskin, 2004; Reville and Eiselt, 2005; Holt et al, 2008). Such models provide a means of assessing the potential impact of a reconfiguration, both from the perspective of the service users and providers, and can be particularly useful to commissioners who need to make cost-effective decisions in a difficult financial climate. In a healthcare context, geographic models have been used for various applications, ranging from optimising the deployment of ambulances (Brotcorne et al, 2003; Peleg and Pliskin, 2004) to assessing the impact of service closures (McLafferty, 1988).

Minor Injury Units (MIUs) offer urgent care services for a subset of injuries that are not serious or life-threatening (Beales and Baker, 1995). However, it has been found that many patients who attend MIUs present with conditions that would be better served elsewhere (Dolan and Dale, 1997), either because their condition is more serious and should be referred to an A & E department or, more commonly, because their condition is not covered by the remit of a MIU, and instead they should be assessed by a General Practitioner. Consequently, questions have been raised as to the effectiveness of MIUs (Dolan and Dale, 1997; Leaman, 1999) as well as the methods of educating the public about those injuries that are appropriate for presentation at such units (Sanders, 2000).

A commissioning group in South West England was considering the closure of four Minor Injury Units in the area in order to reduce costs. Recognising that a significant percentage of attendances to MIUs in the area would have been better served elsewhere, they planned to combine these closures with strategies to reduce unsuitable MIU attendances. However, they wanted to understand how patient travel times and attendances at the remaining MIUs might be impacted if the closures went ahead but there was no reduction to unsuitable attendances. In this paper, we describe how we built a geographic model of the existing pre-closure configuration of MIUs, and then adapted this model to predict the impact of the closures.

## **Methods**

### *The Data*

In order to respect the confidentiality of the commissioning group in this study, we refer to the seven Minor Injury Units as MIUs A to G, and the two Walk-in Centres (WiCs) as WiC 1 and WiC 2. MIUs D-G are the MIUs that were identified for closure. WiC 1 is located at an acute hospital.

We received 90,252 anonymised records of attendance for the seven MIUs and two WiCs in the locality. 89,601 (99%) of these records were obtained from the local Patient First system, and capture attendances from April 2012 to March 2013 at both of the WiCs and four of the seven MIUs (MIUs A-D). These records consisted of the date and time of attendance, the site attended and the postcode sector of the patient's home address. 651 (1%) of the total records related to MIUs E-G, and were obtained from samples of hand-written cards recording attendances. The sample for MIU E was 195 records, representing a three month sample from 2013. The sample for MIU F was 28 records, and again represented a three month sample for 2013. The sample for MIU G was 428 records, representing the eight months of April 2013 and June to December 2013 (inclusive). In all three samples, the home postcode sector of the patient was provided, along with the month of their

attendance for the MIU G sample. To avoid potential skewing of the data, we included only those patients whose Postcode Area denoted that they lived in the locality (90.51% of records), thereby excluding the consideration of travel times of visitors to the region who would not normally use these services. We also excluded any postcodes that were invalid (0.4% of records).

In order to include the samples for MIUs E-G in the model, we extrapolated the samples across a 12-month period, to match the data for MIUs A-D. We analysed the seasonality of the Patient First data for MIUs A-D by calculating seasonal indices (Côté and Tucker, 2001) in order to establish whether there were any strong seasonal patterns in the attendance data over the course of the year. We found only minimal deviation across the year, and therefore, for the MIU E and F samples, we simply quadrupled the data with which we were provided by replicating it a further three times. For the MIU G sample, we excluded April and June 2013, and doubled the six month sample set by replicating it once.

### *Modelling Assumptions*

Based on the results of the data analysis, the availability of data and the objectives of the project, we made a number of assumptions in the model. First, we assume that in the pre-closure configuration, patients attend the MIU or WiC according to the data, but in the post-closure “what if” scenario, patients travel to their nearest MIU or WiC from their home postcode sector, unless it has been closed, in which case they attend the next nearest MIU or WiC. This assumption is supported by our analysis of the data which showed that 80.8% of MIU patients visited their nearest MIU, and 90.1% visited one of their two nearest MIUs (see Table 1).

Second, for simplicity we assume that all patients travel to their chosen MIU or WiC by car. This may underestimate the travel times of those arriving by public transport. Third, we assume that a patient’s car travel time represents the shortest calculated travel time between their home postcode sector and the MIU or WiC, because we do not have data to indicate the location of the patient at

the time they made the decision to attend the MIU or WiC. Fourth, we assume that, all MIUs and WiCs remaining open in the “what if” scenario are available at all times to patients in the model. In reality, not all MIUs are open at all times on all days, and these times could affect a patient’s choice of MIU. Therefore, our model should be considered as an “in-hours” model. Finally, we assume that patients in the model only attend MIUs and WiCs. It is possible that a patient who would have previously visited an MIU might choose to visit their GP instead if their local MIU was closed down. However, our analysis effectively considers a “worst case scenario” of MIU attendances, in which all MIU patients directly affected by the closures are displaced to other MIUs or WiCs.

#### *Car Travel Time Calculations*

In order to calculate the shortest car travel times between each patient’s home postcode sector and each MIU or WiC, we used the MPMileCharter Professional add-in (MPMileCharter; Winwaed Software Technology LLC, TX, USA; [www.milecharter.com](http://www.milecharter.com)) for Microsoft MapPoint (MapPoint; Microsoft Corporation, Redmond, WA, USA; [www.microsoft.com](http://www.microsoft.com)). The resultant travel time calculations were stored in a matrix, and a separate matrix was generated which recorded the number of attendances from each postcode sector to each MIU or WiC. We estimated that 4.22% of local patients would be directly affected by the closures, as this represents the percentage of local patient attendances to MIUs D-G.

Table 1 shows the percentage of MIU patients that attended their nearest and progressively more distant MIU, according to these results.

<b>Relative Closeness of MIU to Home Postcode Sector</b>	<b>Percentage of MIU Patients Attending</b>
Closest MIU	80.81%
2 <sup>nd</sup> Closest MIU	9.31%
3 <sup>rd</sup> Closest MIU	6.82%

4 <sup>th</sup> Closest MIU	1.59%
5 <sup>th</sup> Closest MIU	0.89%
6 <sup>th</sup> Closest MIU	0.43%
7 <sup>th</sup> Closest MIU	0.15%

*Table 1. Percentage of MIU patients attending their nth nearest MIU.*

### *The Model*

We built the geographic model using Microsoft Excel (Excel; Microsoft Corporation, Redmond, WA, USA; [www.microsoft.com](http://www.microsoft.com)), and populated the model using the results from our analysis of the data, and the car travel times calculated using MPMileCharter. For the existing pre-closure scenario (the base case), the model calculates the average travel time across all patients travelling to MIUs and WiCs, and the average travel time across only those patients attending MIUs D-G. These averages are weighted according to the number of attendances from each home postcode sector to each MIU or WiC. Therefore, those postcode sectors with a larger number of attendances to a given MIU or WiC will have a larger influence on the resultant average travel time calculation.

For the post-closure “what if” scenario, the model first calculates the next nearest open MIU or WiC to each of the four closed MIUs D-G. We include WiCs as viable alternatives to MIUs in the model because of public confusion surrounding the unique properties of MIUs (Sanders, 2000). Table 2 shows the two nearest MIUs or WiCs to each of the closed MIUs D-G, the car travel time from the closed MIU to this MIU or WiC, and whether or not they would be open in the post-closure scenario. From these results we can see that, assuming patients would attend the next nearest open MIU or WiC if their nearest MIU is closed, then patients who previously attended MIUs E, F and G would attend MIU B. Patients who previously attended MIU D would attend WiC 2. However, as WiC 1 is also nearby, and is located at the acute hospital which is likely to be better known to the public, we also generated results based on ex-MIU D patients attending WiC 1 instead.

<b>Closed MIU</b>	<b>Nearest MIU or WiC</b>	<b>Car Travel Time (minutes) to Nearest MIU or WiC</b>	<b>Nearest Open?</b>	<b>2<sup>nd</sup> Nearest MIU or WiC</b>	<b>Car Travel Time (minutes) to 2<sup>nd</sup> Nearest MIU or WiC</b>	<b>2<sup>nd</sup> Nearest Open?</b>
<b>MIU D</b>	WiC 2	33	Yes	WiC 1	37	Yes
<b>MIU E</b>	MIU F	17	No	MIU B	21	Yes
<b>MIU F</b>	MIU B	16	Yes	MIU E	17	No
<b>MIU G</b>	MIU B	20	Yes	MIU E	25	No

*Table 2. The nearest and 2<sup>nd</sup> nearest MIU or WiC to each closed MIU in the “what if” scenario, along with the car travel time to these centres, and whether or not they would themselves be open. The shaded cells indicate the next nearest open MIU or WiC for each of the closed MIUs.*

Once the model has calculated the next nearest centres to each closed MIU, it shifts the number of attendances at each closed MIU to each next nearest open MIU. Specifically, the total number of attendances to MIUs E, F and G are added to MIU B, and the total number of attendances to MIU D are added to WiC 2 (or WiC 1 in the alternative “what if” analysis). Attendances to MIUs D-G are then set to 0. After that, weighted average travel times are calculated as in the base case, but using the amended attendance distribution to weight the calculation.

## **Results**

In the existing pre-closure scenario, the weighted average travel time between home and MIU or WiC across all patients is 10.36 minutes per patient, or 8.69 minutes per patient across MIU D-G patients only. In the post-closure “what if” scenario, weighted average travel time across all patients increases to 11.2 minutes per patient, or 28.49 minutes per patient across MIU D-G patients only. If ex-MIU D patients visit WiC 1 instead of WiC 2, the weighted average travel time increases to 11.31

minutes per patient, or 31.09 minutes per patient across MIU D-G patients only. Figure 1 shows the weighted average travel times for each scenario.

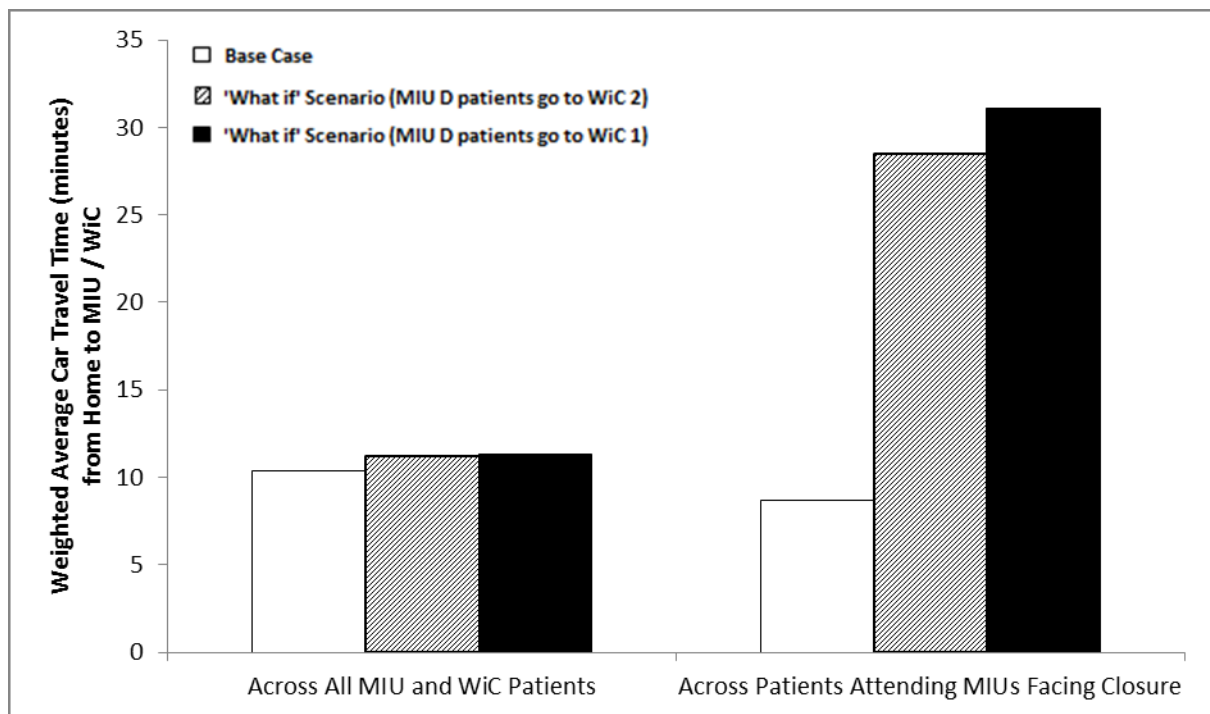


Figure 1. Weighted average travel time per patient for each scenario and across all patients or just those attending MIUs D-G. Empty bars represent base case scenario, line fill bars represent “what if” scenario where ex-MIU D patients go to WiC 2, and solid fill bars represent “what if” scenario where ex-MIU D patients go to WiC 1.

Assuming that patients would visit the next nearest MIU or WiC if their nearest MIU is closed, the model predicts there would be an additional 1,364 patients per year at MIU B, which represents the displacement of patients from MIUs E, F and G, and an additional 2,104 attendances per year at either WiC 1 or WiC 2, representing the displacement of patients from MIU D.

## Discussion

Our model predicts that, if averaged across all MIU patients, the impact of the four MIU closures on travel time from a patient’s home to their nearest open MIU or WiC would be minimal, because only 4.22% of attendances would be directly affected by the closures. However, if we look at only those



patients who would have previously visited one of the closed MIUs, we predict a significant increase in their average travel time of 20 minutes per patient or 22 minutes per patient, depending on whether or not ex-MIU D patients instead attend WiC 2 or WiC 1, respectively. A 20 minute increase in travel time is significant, particularly as the average travel time for these patients before the closures is just 8.7 minutes.

The model also predicts that the closure of MIUs D-G could have a significant impact on the number of attendances seen at MIU B and WiC 1 or WiC 2. MIU B is predicted to see an additional 1,364 attendances per year just from local patients affected by the closures, because it is the nearest alternative service to MIUs E, F and G. Even more problematically, the closure of MIU D could lead to a significant number of additional patients attending the WiC at the acute hospital (WiC 1), as the displacement from MIU D is predicted to be 2,104 attendances per year, and the acute hospital is likely to be better known to patients than the nearby standalone WiC 2. Therefore, there is an associated risk that patients would turn up to the A & E department of the acute hospital instead, increasing the already significant burdens on A & E departments, and undermining the basis for the existence of MIUs and WiCs (Beales and Baker, 1995).

It is very important that the results of the model are understood in the context of the assumptions made. In particular, our results are highly dependent on the assumption that patients would go to their next nearest open MIU or WiC if their usual MIU was closed. This should be a valid assumption because, according to the data, around 80% of MIU patients visit the nearest MIU to their home, and therefore would likely attend their next nearest centre if this MIU was closed. Furthermore, evidence that there is much public confusion around the services offered by MIUs (Sanders, 2000) would lead us to the conclusion that many patients might visit a WiC as an alternative to a MIU if their MIU was closed and a WiC was the next closest service. Nevertheless, it is possible that there are more complex factors influencing patient choice of MIUs and WiCs that are not captured by an

assumption that patients simply visit their nearest service, but in the absence of reliable data about real patients' decision mechanisms we are unable to explore this further.

It is also possible that we have over-estimated the impact of the closures, both in terms of patient travel time and displacement of attendances to other MIUs and WiCs, because patients may choose to visit their GPs instead if their nearest MIU was closed. Indeed, we already know that a significant number of MIU attendances would have been better served by a visit to the patient's GP (Dolan and Dale, 1997), and therefore strategies to minimise unsuitable MIU attendances in combination with the removal of MIU services locally could lead to a higher proportion of appropriate MIU attendances, and overall lower burdens on the remaining MIUs and WiCs in the locality.

Conversely, we may have under-estimated the impact on patient travel time, because we assume that all patients travel by car and take the shortest route. In reality, a number of patients attending MIUs and WiCs may use public transport (Dolan and Dale, 1997), and the journey times of these patients are likely to be longer. Analysis of public transport use amongst MIU patients in the locality could allow for a more detailed representation of patient's home to MIU journeys in the model. However, the utility of this further analysis may be limited, because although we assume that all patients travel by car, we hold this assumption constant across both the base case and "what if" scenarios. Therefore, the relative difference in travel times between the scenarios is likely to be a good indicator of impact, unless the relationship between car and public transport travel time exhibits significant heterogeneity across the locality.

As mentioned earlier in the paper, our analysis should be considered an "in-hours" analysis, because we assume that all open MIUs are available at all times. Inconsistent out-of-hours availability amongst the MIUs in the locality may at least partially account for the 10% of MIU patients who do not visit either the nearest or second nearest MIU to their home. However, we were unable to include out-of-hours behaviours in the model, because of a lack of time of visit data amongst the three MIUs recording attendances on hand-written cards (MIUs E-G).

As the result of our analysis, the local commissioners decided to continue with the closure of MIUs E, F and G, but not to close MIU D, because of the risk of significant additional attendances at the acute hospital, and the substantial additional travel time for these patients to attend another MIU or a WiC. Therefore, this paper demonstrates that geographic modelling and analysis techniques can have an important role in informing decisions about the closure or geographic reconfiguration of health and social care services, and we would argue should be routinely undertaken as a key part of the evidence base for such decisions.

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An anonymised version of the full data used to parameterise the model, along with the full outputs of the model, may be provided on request.

### **Key Points**

- We built a geographic model of patient visits to Minor Injury Units in a locality of South West England, to assess the potential impact of four MIU closures on patient travel time and other MIU and Walk-in Centre attendances
- Our model predicts that there would be a minimal increase in travel time across all patients, but a significant increase amongst those directly affected by the closures
- We predict that the closure of one of the MIUs could lead to significant additional attendances at the acute hospital

- Based on the results of our analysis, the local commissioners decided to close only three of the four MIUs originally planned for closure
- We would encourage others making service closure or geographic reconfiguration decisions to use geographic modelling techniques to inform their decisions

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